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Spatial downscaling of climate variables using three statistical methods in Central Iran

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Abstract: Spatial downscaling methods are widely used for the production of bioclimatic variables (e.g. temperature and precipitation) in studies related to species ecological niche and drainage basin management and planning. This study applied three different statistical methods, i.e. the moving window regression (MWR), nonparametric multiplicative regression (NPMR), and generalized linear model (GLM), to downscale the annual mean temperature (Bio1) and annual precipitation (Bio12) in central Iran from coarse scale (1 km × 1 km) to fine scale (250 m ×250 m). Elevation, aspect, distance from sea and normalized difference vegetation index (NDVI) were used as covariates to create downscaled bioclimatic variables. Model assessment was performed by comparing model outcomes with observational data from weather stations. Coefficients of determination (R^2), bias, and root-mean-square error (RMSE) were used to evaluate models and covariates. The elevation could effectively justify the changes in bioclimatic factors related to temperature and precipitation. All three models could downscale the mean annual temperature data with similar R^2, RMSE, and bias values. The MWR had the best performance and highest accuracy in downscaling annual precipitation (R^2=0.70; *RMSE*=123.44). In general, the two nonparametric models, i.e. MWR and NPMR, can be reliably used for the downscaling of bioclimatic variables which have wide applications in species distribution modeling.

Keywords: Statistical models; Climatic data; Elevation; Spatial resolution; Temperature; Precipitation

Introduction

Climate variables are valuable information resources in the understanding of environmental and ecological systems. While these variables can be easily extracted from weather stations and remote sensing data, the limited number and uneven distribution of weather stations has turned the production of reliable climate maps into a challenge. Collecting precipitation data at fine

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spatial scales is actually challenging (Xie and Arkin 1996; Wilheit 1986) due to the spatial and temporal variability of precipitation (Hu et al. 2013) and scattered distribution of weather stations. Remote sensing data can hence serve as an alternative source of comprehensive information in producing climate maps (Zhu et al. 2017). Bioclimatic variables such as mean annual temperature (Bio1) and annual precipitation (Bio12) are derived from the monthly temperature and rainfall values in order to generate more biologically meaningful variables. Bioclimatic variables have found wide applications in climate and ecological studies, particularly in species distribution modeling. The global values of these variables have been interpolated using geostatistical methods and can be available at the Worldclim website (www.worldclim.com) with different spatial resolutions (from 1 to 344 km). However, owing to their coarse spatial resolution, these maps are not useful for local studies (Davis et al. 2010). Since climate data with fine spatial scale is essential for the understanding of local and regional systems, stable and reliable measurements will depend on data conversion and scaling. Spatial downscaling is a method of deriving fine-scale climate information from data with coarse spatial resolution (Flint and Flint 2012; Park 2013). Downscaling can be either dynamical or statistical (Hewitson and Crane 1996). Dynamical downscaling uses numerical analysis methods to solve the equations governing the air mass in finer networks of the general circulation model (GCM) (Haltiner and Williams 1980). Statistical downscaling methods seek to establish empirical-statistical relationships between independent (predictor) and dependent (predicted) variables. Considering their simplicity, high speed, and cost-effectiveness, these methods are suitable for regional downscaling (Fowler et al. 2007; Xu 1999).

A variety of statistical methods, including regression analysis and straight linear interpolation, are used in statistical downscaling (Weichert and Burger 1998). Straight linear interpolation can be regarded as the simplest technique (Mimikou et al. 2000; Arnell 2002). Bioclimatic variables can be downscaled by using fine-scale atmospheric or surface patterns/indices as independent variables. Statistical approaches to spatial downscaling work based on the fact that the spatial patterns of climatic factors (i.e. precipitation and temperature) are related to a number of covariates, including elevation and the NDVI, which generally has high spatial resolution. The incorporation of finer-scale environmental covariates into regression models can improve the quality of downscaling results and the spatial resolution of climate data (Wotling et al. 2000; Immerzeel et al. 2009). In recent decades, the increased power of software applications, along with easier access to climate datasets and geostatistical methods, has facilitated the production of high-resolution climate maps (Running et al. 1987; Goovaerts 1997; Remy et al. 2009). Jia et al. (2011) and Park (2013) utilized statistical methods, with elevation and the NDVI as covariates, to downscale data from the Tropical Rainfall Measuring Mission (TRMM). They applied multiple regression analysis to establish relationships between climate data and covariates at a coarse scale. They then used environmental covariates to detail the obtained model to a finer scale and produce climate variables with smaller pixel size. Xu et al. (2015) adopted regression and multifractal methods, with elevation, latitude, and longitude as covariates, to downscale the pixel size of precipitation layers from 0.25° to 0.01°. Immerzeel et al. (2009) used an exponential relationship between the NDVI and precipitation data from the TRMM to downscale precipitation layers from 28 km to 1 km. Fang et al. (2013) developed a downscaling method based on the effects of local topography and pre-storm meteorological conditions and reduced the pixel size of precipitation data from the TRMM to 1 km × 1 km. Flint LE and Flint AL (2012) applied multiple regression and a combination of a spatial gradient and inverse-distance-squared (GIDS) weighting to downscale bioclimatic variables.

Statistical models generally seek to predict an outcome variable based on its correlations with a number of predictors. The generalized linear model is a global (parametric) statistical model with a predefined function between the outcome variable and the predictor. The model is, in fact, fitted for all data and all points receive equal weight during the analysis. On the contrary, local (non-parametric) statistical models, including the MWR and the NPMR, do not make any assumptions about the shape of the response curve, i.e. the curve shape may change at different parts of the data space. The NPMR and GLM are widely used for determining species response curves and habitat suitability in species distribution modeling (McCune 2006). GLM has also been utilized in spatial downscaling.

The present study aimed to compare the performance of a common method, “generalized linear model (GLM)” with two relatively novel statistical methods including “moving window regression (MWR)” and “nonparametric multiplicative regression (NPMR)” in downscaling of bioclimatic data. Identification of the most appropriate method will be beneficial to not only data generation for areas without a weather station and mountain environments, where meteorological stations are often sparse and the morphology rather rugged, but also the analysis and ecological modeling of various phenomena, particularly species distribution.

1 Study Area

The study area is located in central Iran (30°31' - 34°45' N and 49°4'- 55°46' E) and covers a vast area of Zagros Mountains. The elevation varies from 50 to 4251 m. The study area includes different landform units such as mountains (25%), plateaus and upper terraces (20%), Hills (15%) and plains (40%). The mean annual temperature varies between 1.7°C in west high mountains to 26°C in east plains. Annual precipitation also varies from 53 mm to 455 mm, respectively (Figure 1).

2 Methodology

2.1 Spatial data layers

The digital elevation model (DEM) was derived from Global 30 Arc-Second Elevation (GTOPO30). The aspect layer was produced from digital elevation model in ArcGIS 10.1. It was converted into a continuous variable using Eq.(1). The new aspect layer varied between zero (azimuth 225°) and two (azimuth 45°) (Beers et al. 1966).

$$\text{Converted aspect} = \text{Cos}\,(45 - \text{aspect}) + 1 \qquad (1)$$

Map of distance from sea was generated based on coastline of Persian Gulf using ArcGIS 10.1. The normalized difference vegetation index (MOD13A2) data for every 16 days from May 2000 to September 2010 were extracted from MODIS images with 1 km resolution. The average NDVI during 10 years was used as an auxiliary variable to downscale the bioclimatic variable (annual precipitation).

Bioclimatic variables, including annual mean temperature (Bio1) and annual precipitation (Bio12), were extracted from the Worldclim database (Hijmans et al. 2005). They were downscaled to various resolutions (500-m, 250-m and 90-m) with different auxiliary environmental variables (covariates) such as distance from sea,

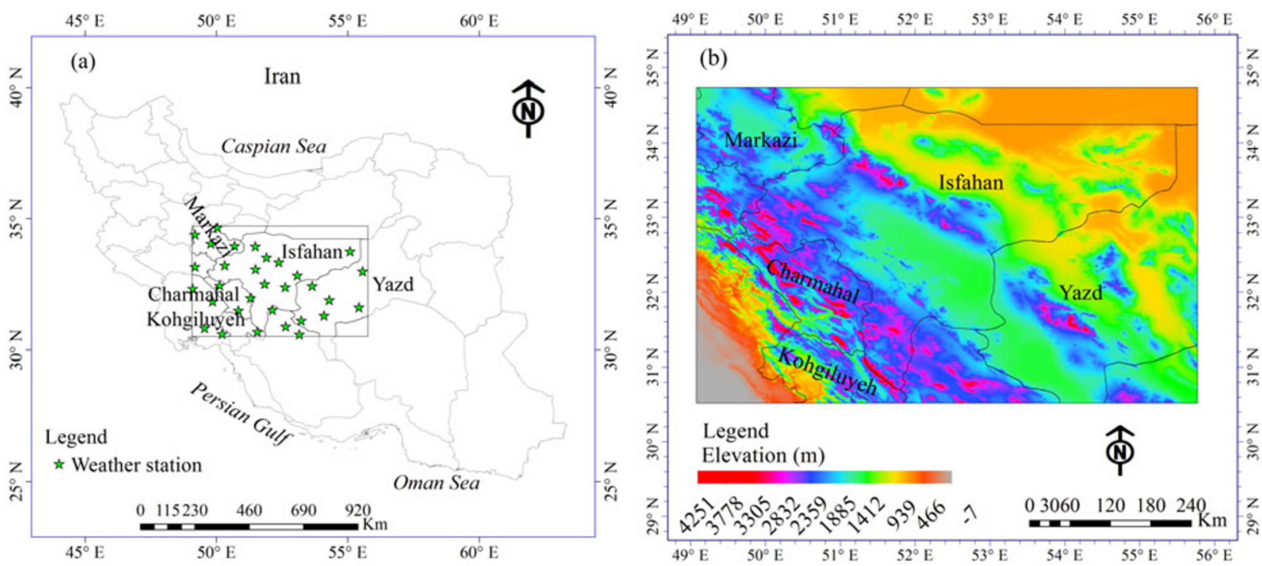

Figure 1 Study area and distribution of weather stations (a) and elevation (Grid size=1km) (b).

aspect, NDVI and elevation by three statistical methods (GLM, NPMR and MWR). Importance of the covariates was determined using R^2, bias and RMSE indices. The best grid resolution was selected based on minimized error i.e. difference between observed values in weather stations and predicted values from produced maps.

2.2 Statistical methods

2.2.1 Moving Window Regression

In this method, a window was first defined based on specific width and height. It was then moved over the whole study area, row-by-row and column-by-column (Figure 2). This process was simultaneously performed over a digital elevation model (DEM) and the desired climate grid (e.g. Bio1). At each window position, the elevation and climate data (e.g. Bio1) were sampled at all grid cells covered by the window and a linear regression was applied to the sampled pairs. The results, i.e. lapse rate and intercept per window position, were recorded in the central cell of each window position. A spatial interpolator (IDW) was then applied to the new grids to downscale them to a fine-scale DEM (250 m), which served as the basis for the final fine-scale climate grids. The detailed DEM and regression parameters (i.e. local lapse rate and intercept) were ultimately used to reproject these grids to actual, fine-scale elevation values (Figure 2, Zimmermann and Roberts 2001). Due to the limited changes in the temperature lapse rate and intercept within short distances, a window size of 25 pixel× 25 pixel was selected in the downscaling

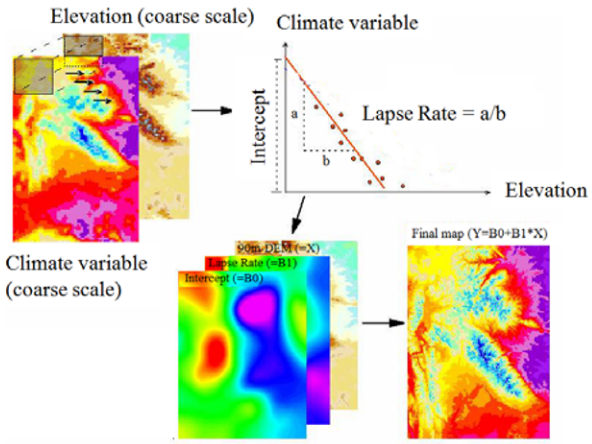

Figure 2 Illustration of the downscaling procedure using moving window regression technique (Zimmermann and Roberts 2001).

of temperature maps. Since large changes in the precipitation lapse rate were observed with changes in topography within a landscape, a window size of 15 pixel × 15 pixel was used for precipitation downscaling. This process was performed by mowinreg_pc software (Zimmermann and Roberts 2001).

2.2.2 Nonparametric Multiplicative Regression

NPMR produces complex interactions among several ecological factors multiplicatively, assuming a local response throughout the ecological sample space. Within a moving window the relationship between every data point and a target point is fitted by weighting non-target points according to their ecological distance from the target point. The target point is a sample unit for which an estimate is produced by the developing model and non-target points are the remaining set of sample units. In this study, NPMR was applied to clarify the existing relationships between bioclimatic variables and covariates. Since a local model and a kernel function are required for the application of NPMR (McCune et al. 2003), a local mean estimator and the Gaussian kernel function were used in this study. The form of the Gaussian function is based upon the standard deviation of each environmental variable (tolerance). The significance of each variable and the overall model quality (xR^2) were evaluated through different measures. The xR^2 values, calculated as the size of the cross-validated residual sum of squares in relation to the total sum of squares, reflected the variability obtained through the best fit model (Bowman and Azzalini 1997). NPMR estimates response curves (Gaussian or sigmoid curves), which exhibit the response of ecological characteristics to environmental gradients.

During NPMR modeling, 8100 pixels, which covered the whole target space, were randomly selected using ArcGIS 10.1 (Esri, USA). The values of covariates (independent variables) and bioclimatic variables were then extracted with a pixel size of 1 km. The NPMR model was fitted using the local Gaussian approach in HyperNiche software package (MjM Software Design, USA) and the model with the highest R^2 coefficient was selected as the best fitting model (McCune and Mefford 2004). Afterward, the digital elevation map with grid cell equal to 250m was entered into the model and the bioclimatic variables were downscaled and output maps were produced.

2.2.3 Generalized Linear Model

The bioclimatic factors (dependent variables) and covariates (independent variables) were considered as GLM inputs. After developing a linear regression model between covariates and bioclimatic variables, the mathematical model was generalized to the geographical space and the bioclimatic variables were downscaled to a 250-m pixel size using the covariate maps at 250-m resolution.

2.3 Model assessment

Accuracy of the MWR, NPMR, and GLM, were determined using observational data (monthly temperature and precipitation data during 1998-2010) obtained from 31 weather stations of Iran Meteorological organization (Figure 1) and estimated values from three statistical models. The downscaled maps were validated using the coefficient of determination (R^2), the root-mean-square error (RMSE), and bias indices (Eqs. 2-4).

$$R^2 = \frac{\sum_{i=1}^{n}[P(x_i) - \overline{M}(x)]^2}{\sum_{i=1}^{n}[M(x_i) - \overline{M}(x)]^2} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[P(x_i) - M(x_i)]^2} \tag{3}$$

$$Bias = \frac{\sum_{i=1}^{n} P(x_i)}{\sum_{i=1}^{n} M(x_i)} - 1 \tag{4}$$

where n is the total number of weather stations and $P(x_i)$ and $M(x_i)$ are respectively the downscaled and observed values of the bioclimatic factor at the i^{th} station.

3 Results

Results of grid size and covariate selection (Table 1 and 2) showed that elevation at a spatial resolution of 250-m (DEM 250) is the best covariate variable in downscaling process due to higher coefficients of determination (R^2) and lower root-mean-square error (RMSE).

3.1 Moving window regression

The coefficients of determination of the best-fitting model varied from 0.90 to 0.98 for the annual mean temperature (Bio1) and 0.70 to 0.95 for annual precipitation (Bio12). According to the results of downscaling based on the MWR, the annual mean temperature in the study area was 1.7°C-26°C in the coarse scale (1-km) and 1°C-25.9°C in the fine scale (250-m) (Figure 3a and b). Evaluating the surface distribution of the mean annual temperature data showed that the 0°C-5°C

Table 1 Validation of downscaled annual precipitation (Bio12) with the three downscaling approaches (moving window regression (MWR), nonparametric multiplicative regression (NPMR), generalized linear model (GLM)) using different grid sizes

Approach	Covariate	Index		
		R^2	Bias	RMSE
MWR	DEM250 m	0.7	-0.321	123.44
	DEM90 m	0.69	-0.39	226.58
	Dem500 m	0.67	-0.39	227.45
NPMR	DEM250 m	0.482	-0.318	143.955
	DEM90 m	0.45	-0.345	-225.48
	Dem500 m	0.48	-0.4	249.62
GLM	DEM250 m	0.5	-0.313	153.65
	DEM90 m	0.52	-0.4	257.5
	Dem500 m	0.46	-0.4	258.7

Table 2 Validation of downscaled annual precipitation (Bio12) with the three downscaling approaches using different covariates

Approach	Covariate	Index		
		R^2	Bias	RMSE
MWR	Dis.	0.67	-0.27	210.86
	Aspect	0.62	-0.39	225.37
	NDVI	0.71	-0.39	227.10
	DEM(250m)	0.70	-0.321	123.44
NPMR	Dis.	0.41	-0.04	215.63
	Aspect	0.03	-0.43	268.22
	NDVI	0	-0.53	283.98
	DEM (250m)	0.482	-0.318	143.955
GLM	Dis.	0.48	-0.22	230.13
	Aspect	-0.03	-0.44	269.72
	NDVI	0.18	-0.04	245.90
	DEM(250m)	0.500	-0.313	153.65

Notes: RMSE = Root-mean-square error; NDVI = Normalized Difference Vegetation Index; DEM = Digital Elevation Model; MWR = Moving window regression; NPMR = Nonparametric multiplicative regression; GLM = Generalized linear model; Dis. = Distance from sea.

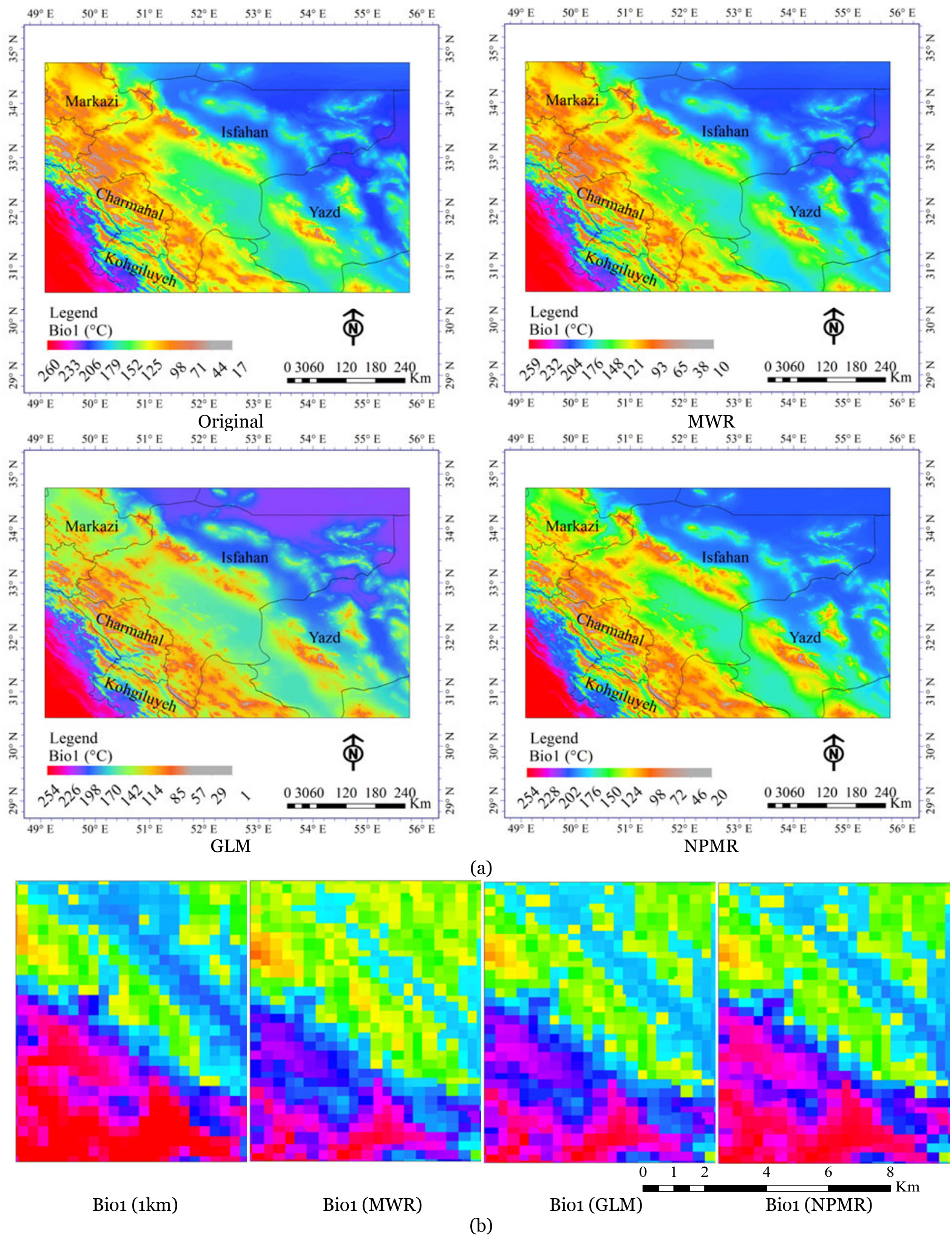

Figure 3 Original (1 km) and downscaled (250 m) annual mean temperature (Bio1), using moving window regression (MWR), nonparametric multiplicative regression (NPMR), and generalized linear model (GLM) methods (a) and enlarged maps from a same subregion (b). Bio1 is temperature data multiplied by 10.

and 16°C-20°C classes had the minimum and maximum area, respectively (Table 3). The annual precipitation also ranged between 53 and 455 mm in coarse scale and between 50 and 456 mm in the fine scale (Figure 4a and b). Moreover, the 0-100 and 401-500 mm precipitation classes covered the largest and smallest parts of the study area, respectively (Table 3).

Table 3 Bioclimatic variable classes and their occupied area under three downscaling methods – moving window regression (MWR), nonparametric multiplicative regression (NPMR), generalized linear model (GLM)

Bioclimatic variable	Class	Occupied area (%)			
		1 km	MWR	NPMR	GLM
Bio1(°C)	0-5	0.23	0.23	0.15	0.25
	6-10	6.81	6.57	4.14	5.45
	11-15	31.40	31.63	35.31	34.29
	16-20	46.04	45.38	43.56	39.27
	21-26	15.53	16.19	16.84	20.73
Bio12(mm)	0-100	35.85	35.01	7.83	0
	101-200	32.54	33.32	69.41	96.70
	201-300	18.40	18.30	19.87	3.30
	301-400	11.65	11.85	2.88	0
	401-500	1.56	1.53	0	0

3.2 Nonparametric multiplicative regression

The coefficients of determination of the best-fitting model for the annual mean temperature (Bio1) and annual precipitation (Bio12) were 0.95 and 0.40, respectively. The tolerance for the mentioned factors was 83.88. The annual mean temperature of the study area was 1.7°C-26°C in the coarse scale and 2°C-25.4°C in the fine scale (Figure 3a and b). The 16°C-20°C and 0°C-5°C temperature classes covered the largest and smallest parts of the study area, respectively (Table 3). The annual precipitation also ranged between 53 and 455 mm in the coarse scale and between 97 and 376 mm in the fine scale (Figure 4a and b). The largest and smallest parts of the study area were covered by 101-200 and 301-400 mm precipitation classes, respectively (Table 3).

3.3 Generalized linear model

In this approach, the coefficients of determination for the annual mean temperature (Bio1) and annual precipitation (Bio12) were 0.94 and 0.05, respectively (Figure 5a and b). The annual mean temperature of the study area was 1.7°C-26°C in the coarse scale and 0.1°C-25.4°C in the fine scale (Figure 3a and b). The largest and smallest areas were occupied by the 16°C-20°C and 0°C-5°C temperature classes, respectively (Table 3). The annual precipitation also ranged between 53 and 455 mm in the coarse scale and between 115 and 247 mm in the fine scale (Figure 4a and b). The largest and smallest parts of the study area were covered by 101-200 and 201-300 mm precipitation classes, respectively (Table 3).

3.4 Response curves of bioclimatic variables to elevation

Response curves of bioclimatic variables to elevation indicated that the annual mean temperature (Bio1) decreased with increasing elevation (Figure 6). The response of annual precipitation (Bio12) to elevation had a Gaussian curve with minimum precipitation (100 mm) occurring at an elevation of about 1200 m. Precipitation then increased with increasing elevation and reached its maximum (400 mm) at 4000 m altitude (Figure 6). Areas with lower elevations (< 1200 m) contained Khouzestan Plain which had greater precipitation owing to its proximity to the sea.

3.5 Statistical model comparison

Table 4 presents the statistical indices required for accuracy assessment and validation of the downscaled maps based on observational data from 31 weather stations in the study area. The highest correlation coefficient (0.96) was detected between observational data and the annual mean temperature (Bio1) downscaled based on the MWR. The lowest bias and RMSE belonged to the GLM and NPMR, respectively.

The observational precipitation data had the high correlation coefficient (0.70) with the mean annual precipitation (Bio12) downscaled using the MWR. The same method also had the lowest RMSE. The least bias was seen when the GLM was applied.

4 Discussion

Climate factors play a major role in ecological studies of plant species (such as species

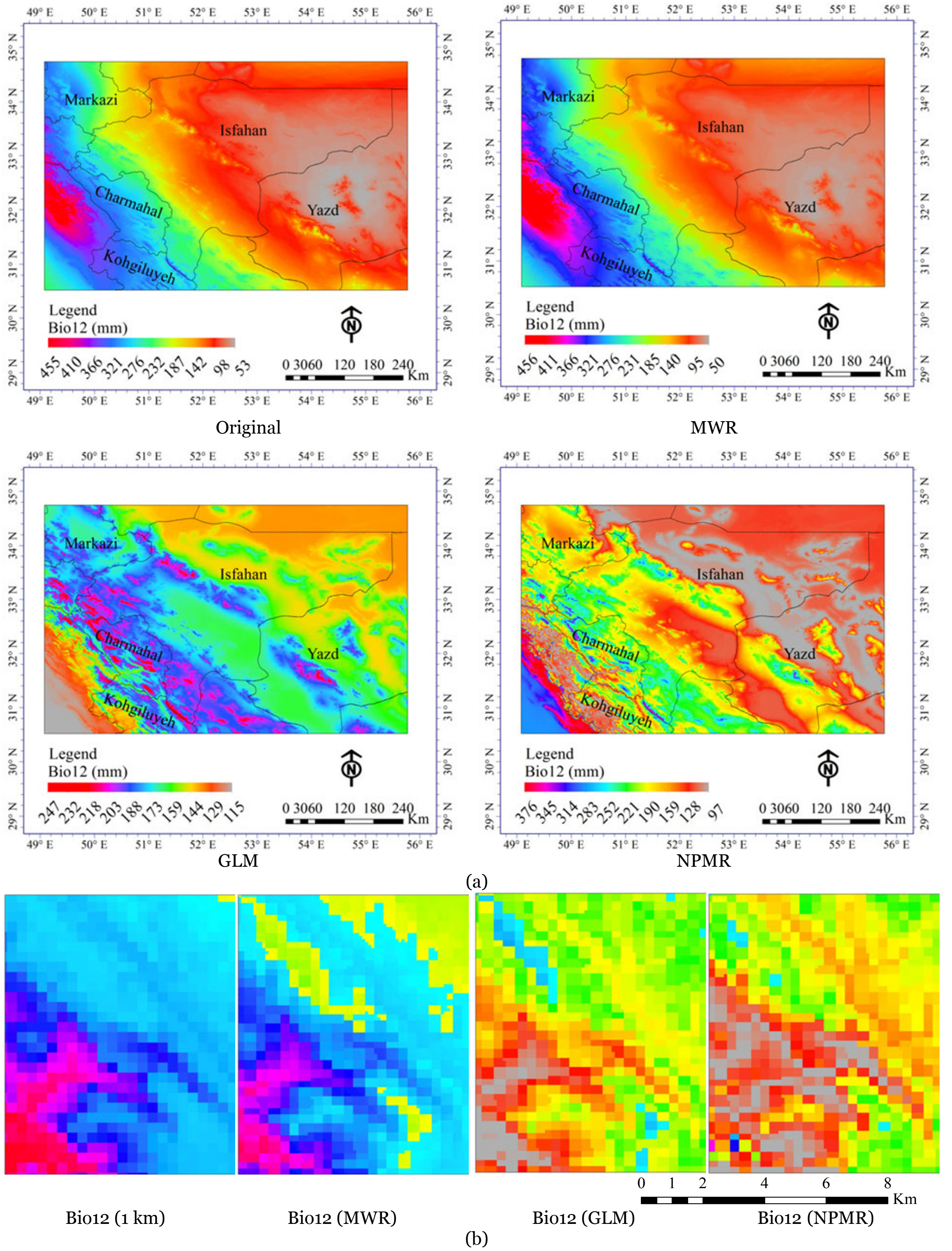

Figure 4 Original (1km) and downscaled (250 m) annual precipitation (Bio12), using moving window regression (MWR), nonparametric multiplicative regression (NPMR), and generalized linear model (GLM) methods (a) and enlarged maps from a same subregion (b).

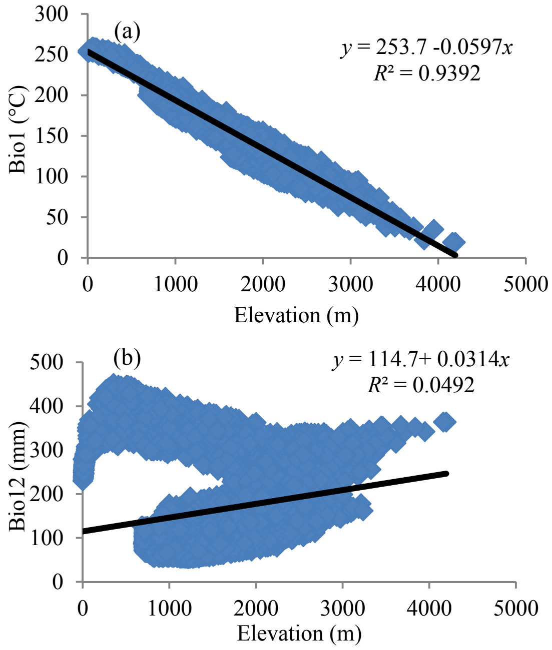

Figure 5 Generalized Linear Regression established to predict annual mean temperature (Bio1) (a) and annual precipitation (Bio12) (b) using elevation (1-km grid cell) as predictive variable. Bio1 is temperature data multiplied by 10.

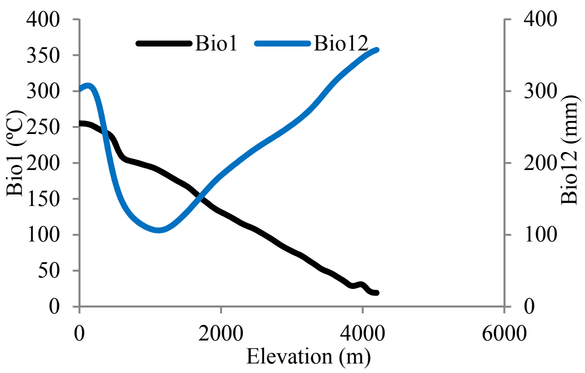

Figure 6 Response curves of annual mean temperature (Bio1) and annual precipitation (Bio12) in relation to elevation (Grid size = 1 km). Bio1 is temperature data multiplied by 10.

Table 4 Validation of downscaled bioclimatic variables (Bio1 and Bio12) with the three downscaling approaches using observation data from weather stations

Approach	Index	Bio1	Bio12
Moving window regression	R^2	0.96	0.70
	Bias	-0.025	-0.321
	RMSE	14.136	123.44
Nonparametric multiplicative regression	R^2	0.852	0.482
	Bias	0.012	-0.318
	RMSE	13.105	143.955
Generalized linear model	R^2	0.851	0.500
	Bias	0.005	-0.313
	RMSE	14.08	153.65

distribution modeling and research on plant species abundance and production) and water resource management. Considering the significance of the spatial scales of environmental layers in the clarification of ecological processes, their careful selection is necessary for the analysis of species-environment relations (Wiens 1989). It is also critical to determining the performance and accuracy of the results of species distribution models. However, the existing environmental and bioclimatic data are generally at a coarse spatial scale and cannot be used for species distribution modeling at finer scales unless they undergo a spatial downscaling process (Davis et al. 2010). Some statistical approaches use environmental variables, e.g. elevation and vegetation indices, as covariates to downscale bioclimatic variables (Brown et al. 2008).

In this study, three statistical methods, including the MWR, NPMR, and GLM, were utilized to relate elevation with bioclimatic factors (Bio1 and Bio12) at a coarse scale (1 km). The mentioned function was then detailed to a smaller pixel size (250 m) and the bioclimatic data were downscaled using the DEM. Since the obtained results confirmed the potential of the digital elevation map in providing a spatial pattern of bioclimatic factors in central Iran, elevation can be used as a valuable covariate in the downscaling of bioclimatic factors, especially precipitation-dependent variables. Indeed, there is a positive relationship between rainfall and DEM, which is a good explanation for the uplift precipitation effect of mountains (Jia et al. 2011). Xu et al. (2015) used elevation, longitude, and latitude as covariates to downscale TRMM-derived precipitation data. According to their findings, the NDVI failed to accurately determine changes in precipitation. Hence, human activities in agriculture change the spatial distribution of the NDVI and its temporal trend. Therefore the predictability of rainfall through NDVI decreased (Jia et al. 2011). In contrast, some ecological studies have highlighted the relation between the NDVI and precipitation and thus adopted this index in precipitation data downscaling (Immerzeel et al. 2009; Park 2013). Ezzine et al. (2017) reported that NDVI and normalized difference water index (NDWI) rather than distance from sea, can be used to downscale precipitation. Distance from sea could not contribute significantly to the downscaling methods. However, the influence of distance could be important only in the first kilometers near of sea and not over whole of the study area (Ezzine et al. 2017). Zimmermann and Roberts (2001) administered the MWR to downscale temperature- and precipitation-related daily climate maps to 30-m and 250-m scales, respectively. They concluded that although incorporating elevation in the downscaling process led to more accurate maps in a micro topography, a set of other factors was required when downscaling in a large landscape with dramatic topographic changes.

The NPMR downscaled the annual mean temperature and precipitation with coefficients of determination equal to 0.95 and 0.40, respectively. Therefore, this method can accurately downscale annual temperature. The GLM downscaled Bio1 with R^2 = 0.94. Since in this method, elevation could only explain 5 percent of changes in annual precipitation (R^2 = 0.05), the precipitation maps downscaled with GLM are not adequately accurate (Figure 5a and b).

Based on the statistical indices, the MWR had the highest correlation coefficient and the lowest RMSE and was hence the most accurate method for downscaling the bioclimatic maps of annual mean temperature and annual precipitation in the study area. Moreover, considering the correlation coefficient between the bioclimatic data downscaled with the NPMR and the observational data (0.852) and the method's low RMSE, the NPMR can be reliably used for downscaling annual mean temperature (Table 4). However, the NPMR and GLM did not have acceptable performance in downscaling annual precipitation. Regarding to complexity of natural land form patterns in study area, we propose to use local model such as MWR to improve bioclimatic variables such as precipitation and temperature in mountainous and complex terrain. This approach can be particularly useful in mountain areas, where the relationships between topography and climatic variables (precipitation, temperature) are very complex and the climate station network is generally sparse compared to the high spatial variability (Kidson and Thompson 1998; Landman et al. 2001; Timbal et al. 2003; Tryhorn and DeGaetano 2011).

The response curves of annual mean temperature and precipitation to elevation produced by the MWR, NPMR, and GLM were only slightly different. All three methods actually had acceptable consistence at elevations over 1000 m (Figure 7a). However, annual precipitation had different responses to elevation at the 250-m scale, i.e. the results of the MWR and NPMR were more consistent with the original data (1-km spatial resolution). Annual precipitation data downscaled with GLM showed an increasing trend within the elevation range of the study area and had significant differences with not only the original data, but also the results of both the MWR and the NPMR (Figure 7b).

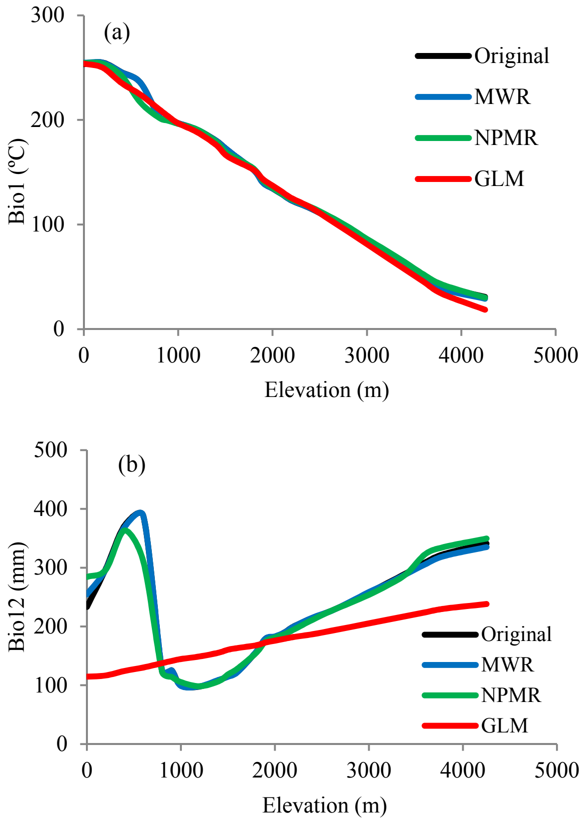

Figure 7 Comparison of annual mean temperature (Bio1) (a) and annual precipitation (Bio12) (b) response to elevation for three spatial downscaling methods – moving window regression (MWR), nonparametric multiplicative regression (NPMR), generalized linear model (GLM). Temperature data are multiplied by 10.

Evaluating the area of distribution of temperature and precipitation classes revealed that the MWR could cover the whole study area (almost identical to the original base map at the 1-km scale). The results of the NPMR were also highly similar to the base maps and the results of the MWR.

However, the GLM categorized 97% of the study area in the 101-200 mm precipitation class which was notably different with the base map and the results of the other two methods. Therefore, the downscaling results of the MWR and NPMR were more consistent with the base map (Table 3).

5 Conclusion

Precipitation and temperature are fundamental climatic variables in ecology, hydrology and meteorology. The lack of high spatial resolution climatic data, which are essential for the ecological modeling and managing of hydrological systems, has triggered many attempts at spatial downscaling. This paper has demonstrated the application of statistical methods to integrate auxiliary fine scale environmental variables (DEM, aspect, distance from sea and NDVI) for downscaling of bioclimatic variables derived from coarse scale. The final downscaled results were validated using weather station observations. DEM could effectively contribute (as a covariate) to the spatial downscaling of bioclimatic variables. The MWR, NPMR and GLM could downscale the mean annual temperature data appropriately. The MWR had the best performance and highest accuracy in downscaling annual precipitation data. By comparing the response curves of annual mean temperature to elevation based on three downscaling approaches, we conclude that the results of the MWR, NPMR and GLM were more consistent with the original data (1-km spatial resolution). However, annual precipitation had different responses to elevation at the 250-m scale, i.e. the results of the MWR and NPMR were more consistent with the original data. The nonparametric models, i.e. MWR and NPMR, can not only be used to downscale bioclimatic variables which have wide applications in species distribution modeling, but also for downscaling the output of Global Circulation Models (GCM) at regional scales. The spatial downscaling approaches presented in this paper can be applied to areas in which ground measurement data are sparse or unavailable. Moreover, the presented spatial downscaling approaches can also be extended to downscaling of other coarse scale climate variables.

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References

Arnell NW (2002) Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: future stream flow in Britain. Journal of Hydrology 270: 195-213. https://doi.org/10.1016/S0022-1694(02)00288-3

Beers TW, Dress PE, Wensel LC (1966) Aspect transformation in site productivity research. Journal of Forestry 64: 691-692.

Brown C, Greene AM, Block P, Giannini A (2008) Review of downscaling methodologies for Africa climate applications. IRI Technical Report 08-05: IRI Downscaling Report, International Research Institute for Climate and Society, Columbia University.

Davis FW, Borchert M, Meentemeyer RL, et al. (2010) Pre-impact forest composition and ongoing tree mortality associated with sudden oak death in the Big Sur region, California. Forest Ecology and Management 259: 2342-2354. https://doi.org/10.1016/j.foreco.2010.03.007

Bowman AW, Azzalini A (1997) Applied Smoothing Techniques for Data Analysis. Clarendon Press, Oxford. p 193.

Ezzine H, Bouziane A, Ouazar D, Hasnaoui MD (2017) Downscaling of open coarse precipitation data through spatial and statistical analysis, integrating NDVI, NDWI, elevation, and distance from sea. Advances in Meteorology 1-20. https://doi.org/10.1155/2017/8124962

Fang J, Du J, Xu W, et al. (2013) Spatial downscaling of TRMM precipitation data based on the orographical effect and meteorological conditions in a mountainous area. Advances in Water Resources 61: 42-50. https://doi.org/10.1016/j.advwatres.2013.08.011

Flint LE, Flint AL (2012) Downscaling future climate scenarios to fine scales for 19 hydrologic and ecological modeling and analysis. Ecological Processes 1(2): 1-15. https://doi.org/10.1186/2192-1709-1-2

Fowler HJ, Blenkinsop S, Tebaldi C (2007) Linking climate change modeling to impacts studies: recent advances in downscaling techniques for hydrologic modeling. International Journal of Climatology 27: 1547-1578. https://doi.org/10.1002/joc.1556

Goovaerts P (1997) Geostatistics for Natural Resources Evalution. Applied Geostatistics, Oxford University Press, NewYork, NY, USA.

Guisan A, Graham CH, Elith J, Huettmann F (2007) Sensitivity of predictive species 20 distribution models to change in grain size. Diversity and Distributions 13: 332-340. https://doi.org/10.1111/j.1472-4642.2007.00342.x

Haltiner G, Williams R (1980) Numerical Prediction and Dynamic Meteorology. John Wiley & Sons. pp 115-120.

Hewitson BC, Crane RG (1996) Climate downscaling:

techniques and application. Climate Research 7: 85-95. https://doi.org/10.3354/cr007085
Hijmans RJ, Cameron SE, Parra JL, et al. (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25: 1965-1978. https://doi.org/10.1002/joc.1276
Hu QF, Yang DW, Wang YT, Yang HB (2013) Accuracy and spatio-temporal variation of high resolution satellite rainfall estimate over the Ganjiang river basin. Science China Technological Sciences 56: 853-865. https://doi.org/10.1007/s11431-013-5176-7
Immerzeel WW, Rutten MM, Droogers P (2009) Spatial downscaling of TRMM precipitation using vegetative response on the Iberian peninsula. Remote Sensing of Environment 113: 362-370. https://doi.org/10.1016/j.rse.2008.10.004
Jia SF, Zhu WB, Lu AF, Yan TT (2011) A statistical spatial downscaling algorithm of TRMM precipitation based on NDVI and DEM in the Qaidam basin of china. Remote Sensing of Environment 115: 3069-3079. https://doi.org/10.1016/j.rse.2011.06.009
Kidson JW, Thompson CS (1998) A comparison of statistical and model-based downscaling techniques for estimating local climate variations. Journal of Climate 11: 735-753. https://doi.org/10.1175/1520-0442
Landman WA, Mason SJ, Tyson PD, Tennant WJ (2001) Statistical downscaling of GCM simulations to stream flow. Journal of Hydrology 252: 221-236. https://doi.org/10.1016/S0022-1694(01)00457-7
McCune B, Berryman SD, Cissel JH, Gitelman AI (2003) Use of a smoother to forecast occurrence of epiphytic lichens under alternative forest management plans. Ecological Applications 13:1110-1123.https://doi.org/10.1890/1051-0761(2003)13[1110:UOASTF]2.0.CO;2
McCune B, Mefford MJ (2004) Hyper Niche. Multiplicative Habitat Modeling. Version 1. MjM Software, Gleneden Beach, Oregon, USA.
McCune B (2006) Nonparametric habitat models with automatic interactions. Journal of Vegetation Science 17: 819-830. https://doi.org/10.1111/j.1654-1103.2006.tb02505.x
Mimikou MA, Baltas E, Varanou E, Pantazis K (2000) Regional impacts of climate change on water resources quantity and quality indicators. Journal of Hydrology 234: 95-109. https://doi.org/10.1016/S0022-1694(00)00244-4
Park NW (2013) Spatial downscaling of TRMM precipitation using geostatistics and fine scale environmental variables. Advances in Meteorology. https://doi.org/10.1155/2013/237126
Remy N, Boucher A, Wu J (2009) Applied Geostatistics with SGeMS: A User's Guide. Cambridge University Press, Cambridge, UK.
Running SW, Nemani RR, Hungerford RD (1987) Extrapolation of synoptic meteorological data in mountainous terrain and its use for simulating forest evapotranspiration and photosynthesis. Canadian Journal of Forest Research 17: 472-483. https://doi.org/10.1139/x87-081
Schuurmans JM, Bierkens MFP (2007) Effect of spatial distribution of daily rainfall on interior catchment response of a distributed hydrological model. Hydrology and Earth System Sciences 11: 677-693. https://doi.org/10.5194/hess-11-677-2007
Timbal B, Dufour A, McAvaney B (2003) An estimate of future climate change for western France using a statistical downscaling technique. Climate Dynamics 20: 807-823. https://doi.org/10.1007/s00382-002-0298-9
Tryhorn L, DeGaetano A (2011) A comparison of techniques for downscaling extreme precipitation over the Northeastern United States. International Journal of Climatology 31: 1975-1989. https://doi.org/10.1002/joc.2208
Xie PP, Arkin PA (1996) Analyses of global monthly precipitation using gauge observations, satellite estimates, and numerical model predictions. Journal of Climate 9:840-858. https://doi.org/10.1175/1520-0442(1996)009<0840:AOGMPU>2.0.CO;2
Xu CY (1999) From GCMs to river flow: a review of downscaling methods and hydrologic modeling approaches. Progress in Physical Geography 23: 229-249. https://doi.org/10.1177/030913339902300204
Xu G, Xu X, Liu M, et al. (2015) Spatial downscaling of TRMM precipitation product using a combined multifractal and regression approach: demonstration for South China. Water 7: 3083-3102. https://doi.org/10.3390/w7063083
Weichert A, Burger G (1998) Linear versus nonlinear techniques in downscaling. Climate Research 10: 83-93. https://doi.org/10.3354/cr010083
Wiens JA (1989) Spatial scaling in ecology. Functional Ecology 3: 385-397. https://doi.org/10.2307/2389612
Wilheit TT (1986) Some comments on passive microwave measurement of rain. Bulletin of the American Meteorological Society 67: 1226-1236. https://doi.org/10.1175/1520-0477(1986)067<1226:SCOPMM>2.0.CO;2
Wotling G, Bouvier C, Danloux J, Fritsch JM (2000) Regionalization of extreme precipitation distribution using the principal components of the topographical environment. Journal of Hydrology 233(1-4): 86-101. https://doi.org/10.1016/S0022-1694(00)00232-8
Zhu W, Lű A, Jia S, et al. (2017) Retrievals of all-weather daytime air temperature from MODIS products. Remote Sensing of Environment 189: 152-163. https://doi.org/10.1016/j.rse.2016.11.011
Zimmermann N, Roberrs DW (2001) Final report of the MLP climate and biophysical mapping project. Swiss Federal Research Institute WSL, Switzerland.